
Optimization Challenges in the Next-Generation Power Grid

Victor M. Zavala

Argonne Scholar
Mathematics and Computer Science Division
Argonne National Laboratory
vzavala@mcs.anl.gov

M. Anitescu, E. Constantinescu, C. Petra, and A. Kannan

ICiS Optimization in Energy Systems Workshop
August 3rd, 2010



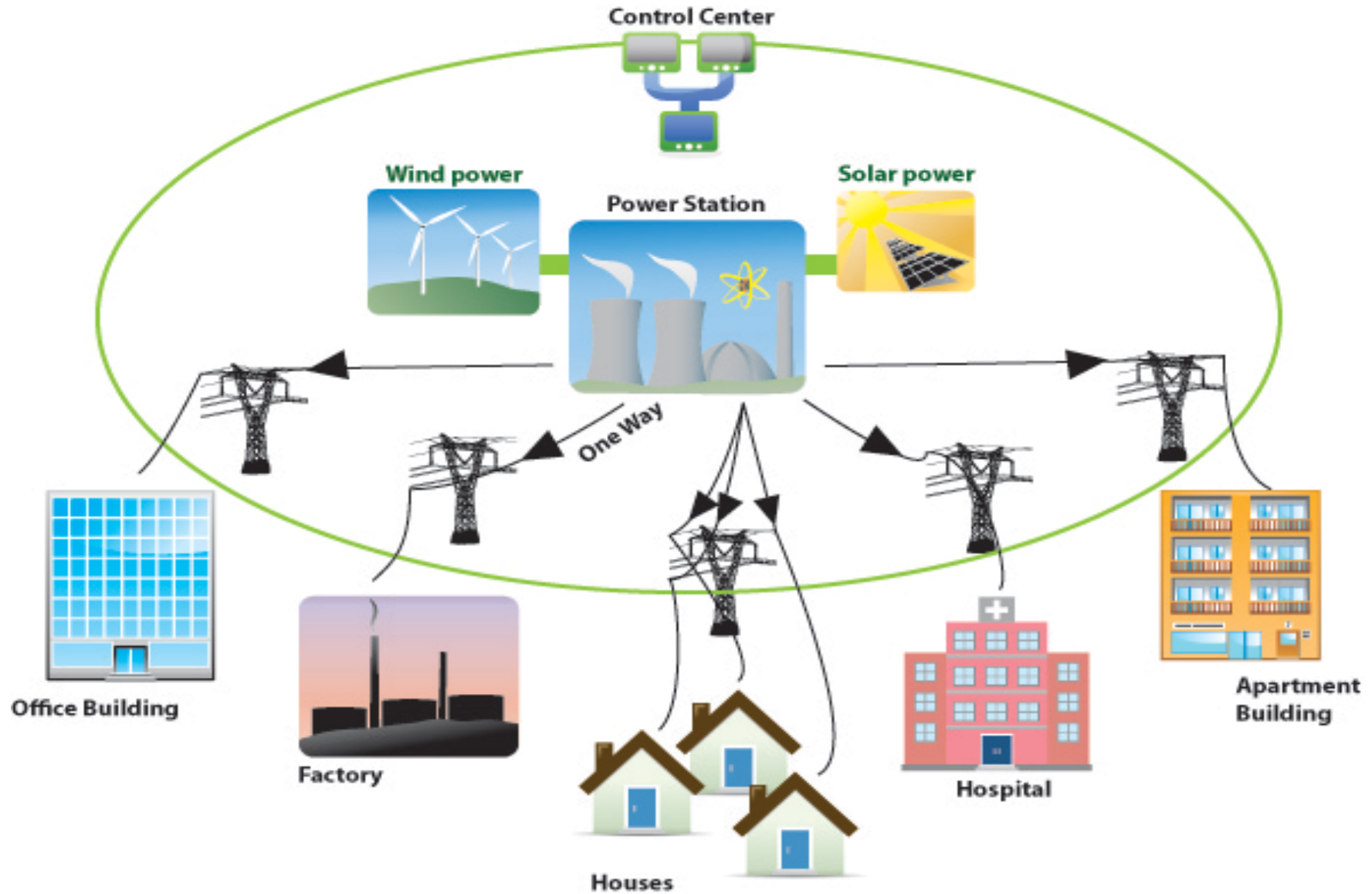
Outline

- 1. Motivation: Next-Generation Grid**
-
- 3. Economic Dispatch**
-
- 5. Building Energy Management**
-
- 6. Dynamic Games and Bidding**
-
- 9. Conclusions and Research Challenges**

Discuss Challenges in Optimization Modeling and Algorithms for Power Grid

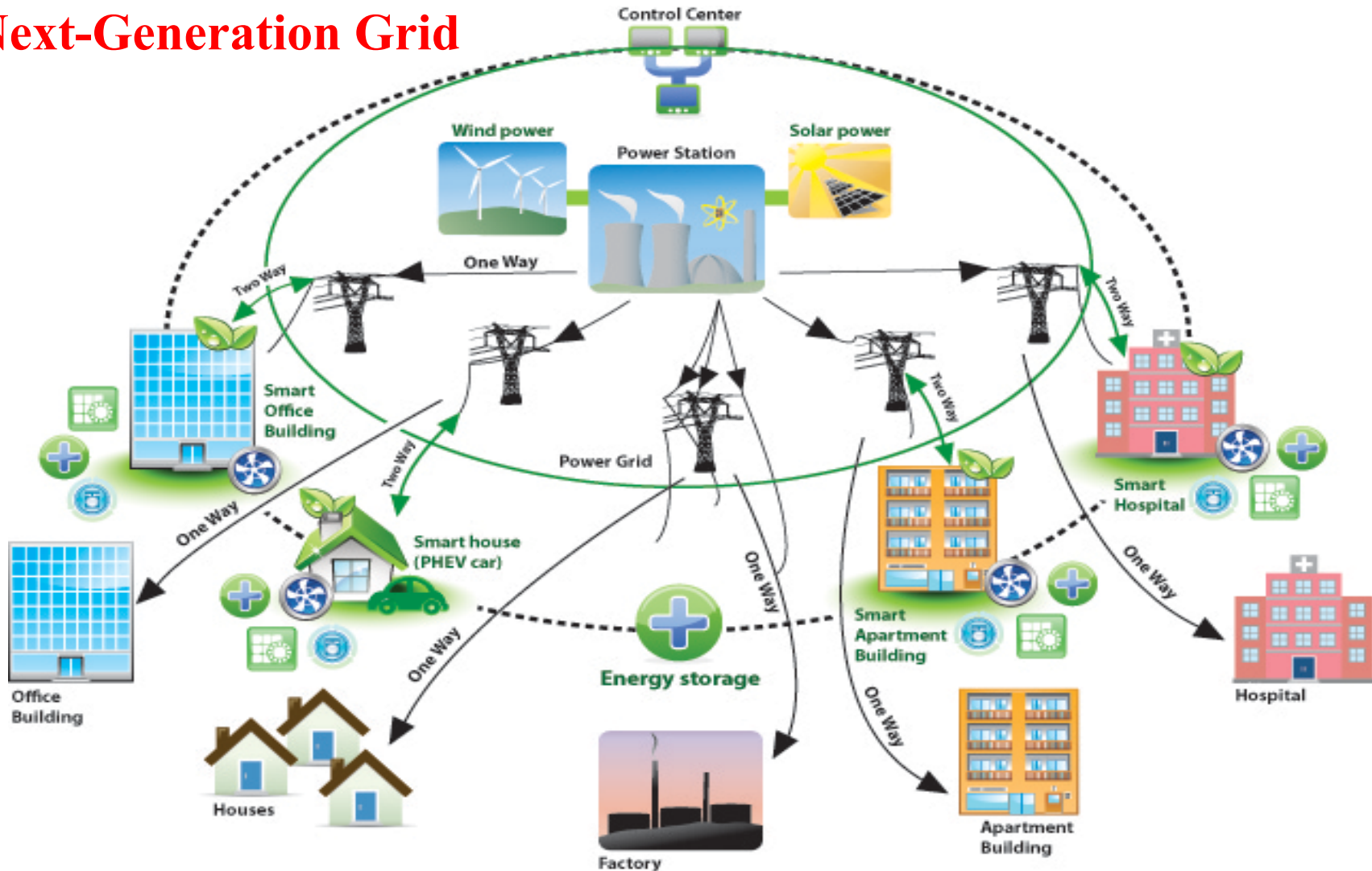
Motivation

Current Grid



Motivation

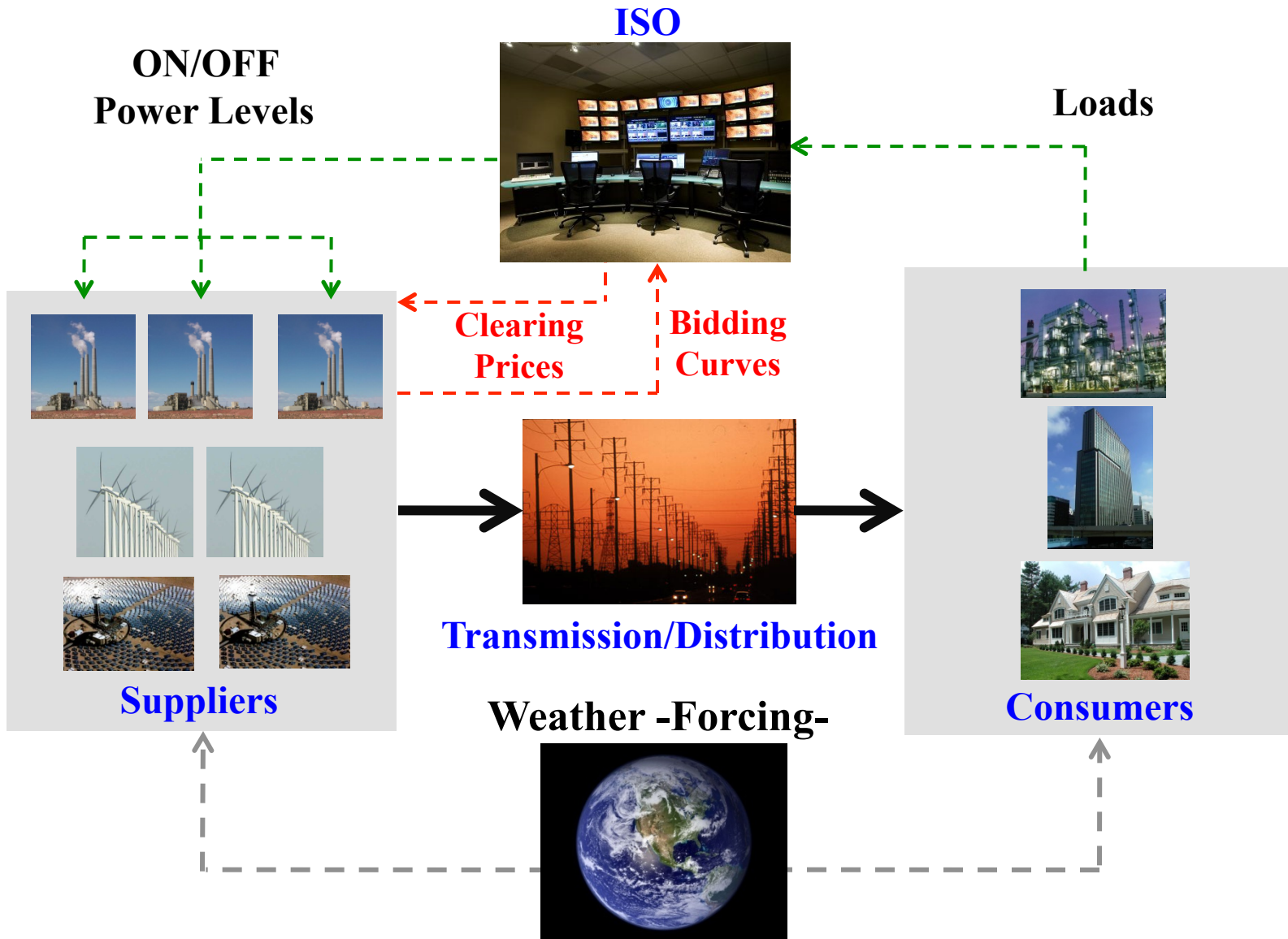
Next-Generation Grid



Major Adoption of Renewables -20-30%-

Distributed Generation and Elastic Demands -Real-Time Pricing-
Distributed Decision-Making – Most Players use Optimization

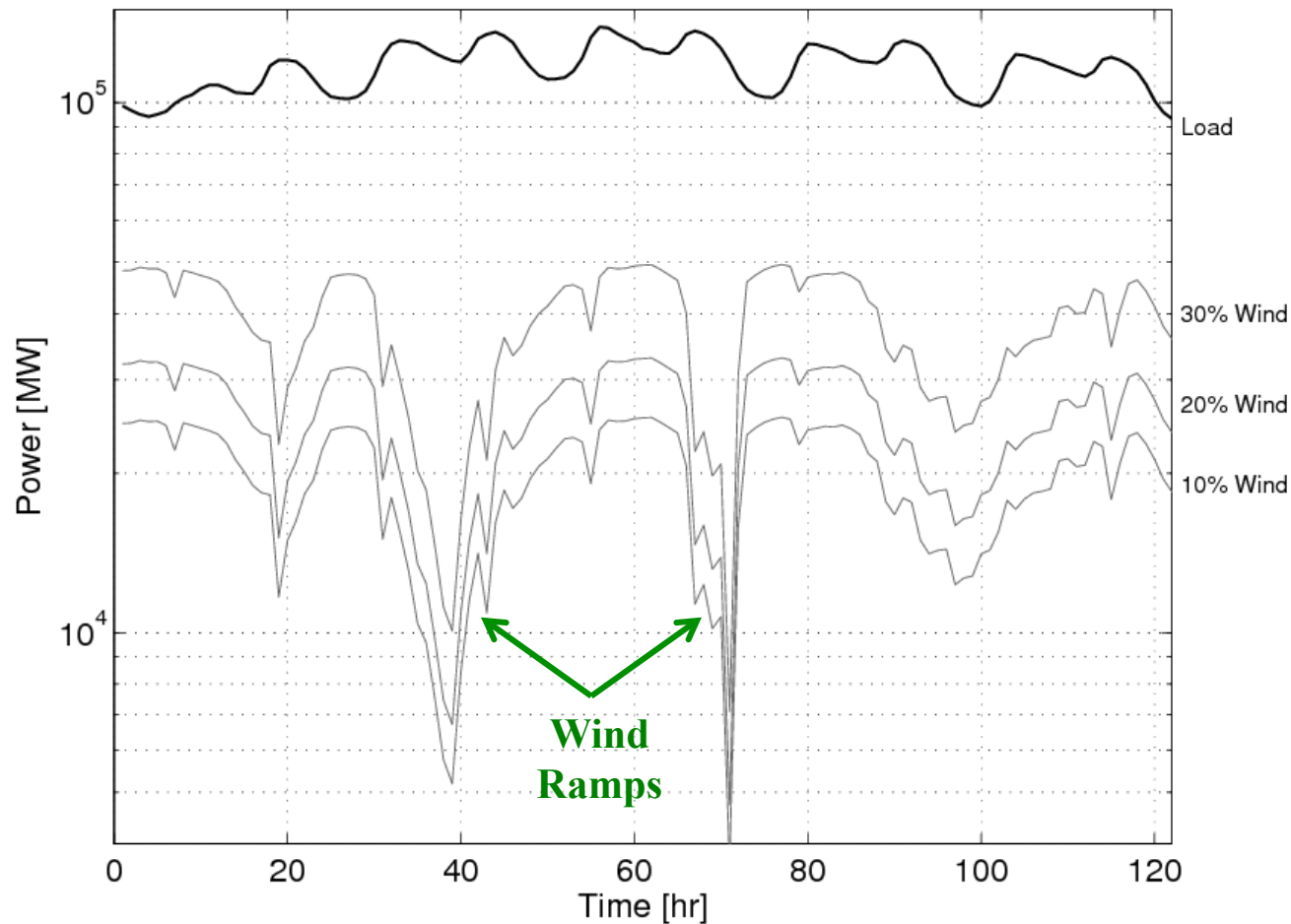
Motivation



Dynamic Forcings -Weather- Drive Markets

Motivation

Dynamic Forcings – Supply (Wind) and Elastic Demands Vary at Higher Frequencies



Capturing Dynamic Effects is Becoming Critical
Longer Forecast Horizons and Faster Updates Needed

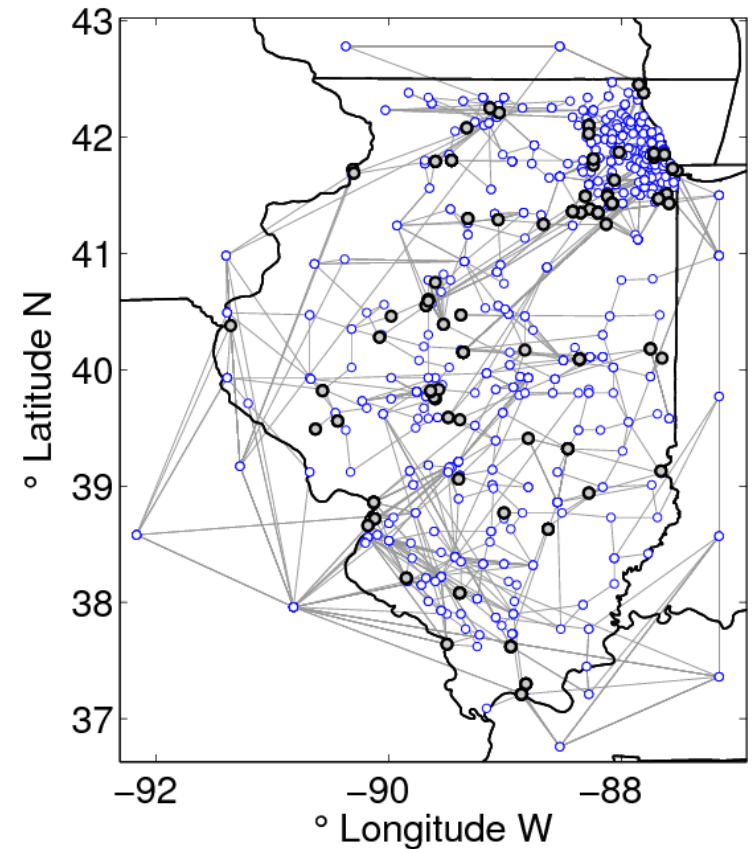
1. Economic Dispatch

Deterministic Economic Dispatch

- **Real-Time Balancing of Demand-Supply, Sets LM Prices** - Updated Every **5 Minutes**
- **Large-Scale LP/QP** - $O(10^4-10^6)$ - Horizon, Ramps, Transmission Constraints

Forecast Horizon

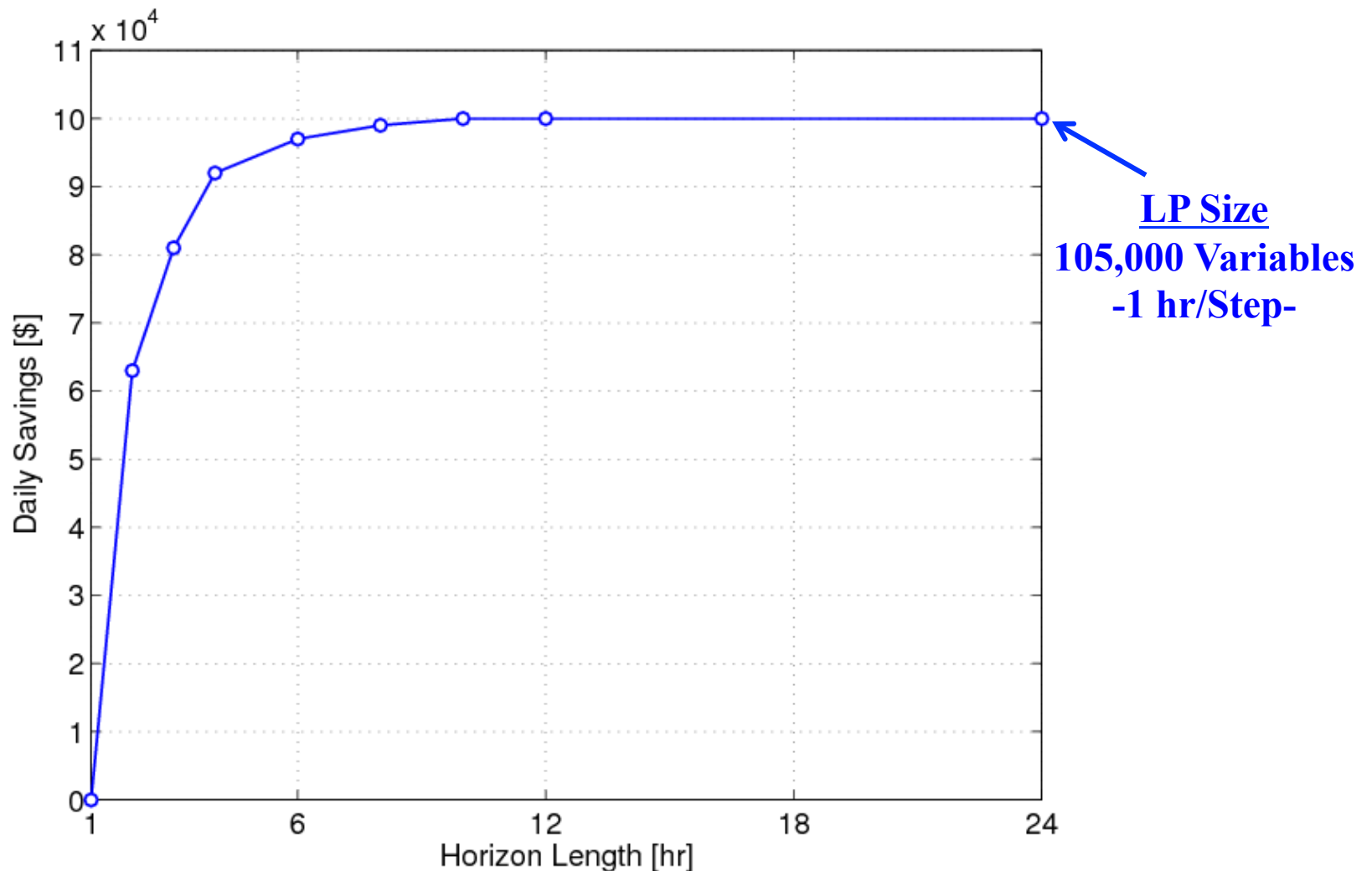
$$\begin{aligned}
 \min \quad & \sum_{k=\ell}^{\ell+N} \sum_{j \in \mathcal{G}} c_j \cdot G_{k,j} \\
 \text{s.t.} \quad & \boxed{G_{k+1,j} = G_{k,j} + \Delta G_{k,j}, \quad k \in \mathcal{T}, j \in \mathcal{G}} \quad \text{Dynamics -Ramps-} \\
 & \boxed{\sum_{(i,j) \in \mathcal{L}_j} P_{k,i,j} + \sum_{i \in \mathcal{G}_j} G_{k,i} = \sum_{i \in \mathcal{D}_j} D_{k,i}, \quad k \in \mathcal{T}, j \in \mathcal{B}} \quad \text{Network} \\
 & P_{k,i,j} = b_{i,j}(\theta_{k,i} - \theta_{k,j}), \quad k \in \mathcal{T}, (i,j) \in \mathcal{L} \\
 & 0 \leq G_{k,j} \leq G_j^{max}, \quad k \in \mathcal{T}, j \in \mathcal{G} \\
 & 0 \leq \Delta G_{k,j} \leq \Delta G_j^{max}, \quad k \in \mathcal{T}, j \in \mathcal{G} \\
 & |P_{k,i,j}| \leq P_{i,j}^{max}, \quad k \in \mathcal{T}, (i,j) \in \mathcal{L} \\
 & |\theta_{k,j}| \leq \theta_j^{max}, \quad k \in \mathcal{T}, j \in \mathcal{B}
 \end{aligned}$$



Benchmark System (Illinois): -1900 Buses, 2538 Lines, 870 Loads, and 261 Generators
 -Daily Generation Cost $\sim \$O(10^8)$

Deterministic Economic Dispatch

Effect of Foresight on Economics - Current Practice 15 Minutes

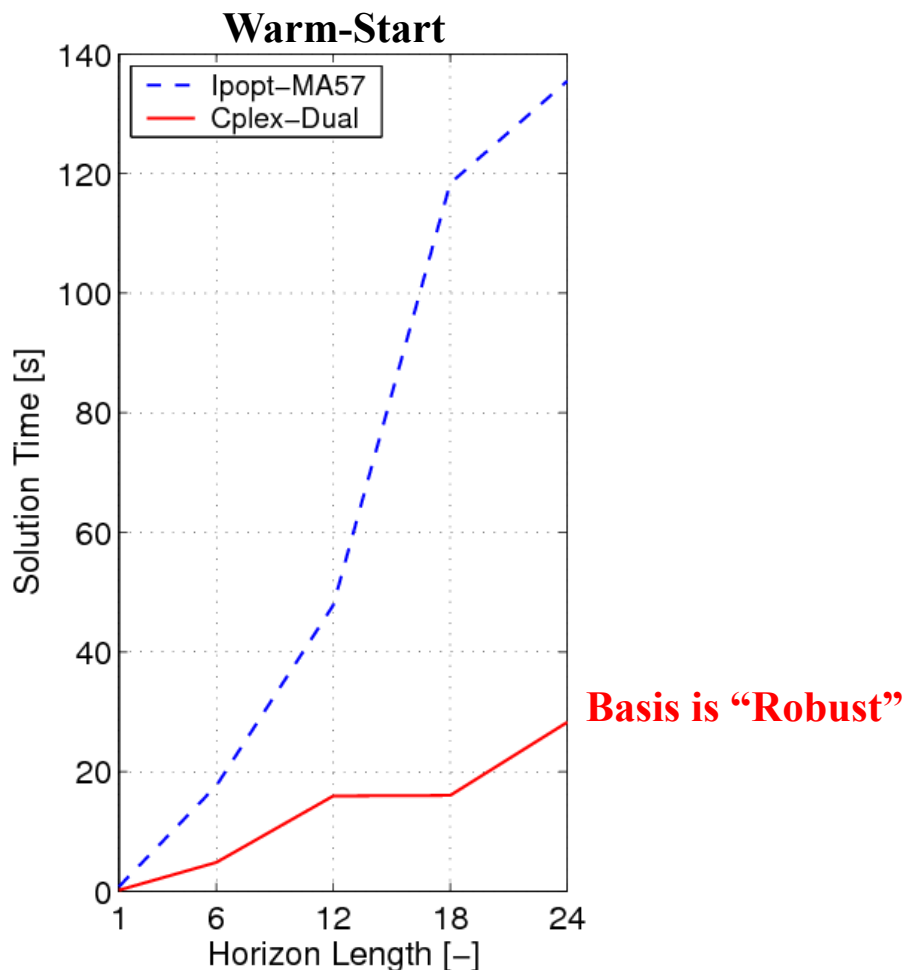
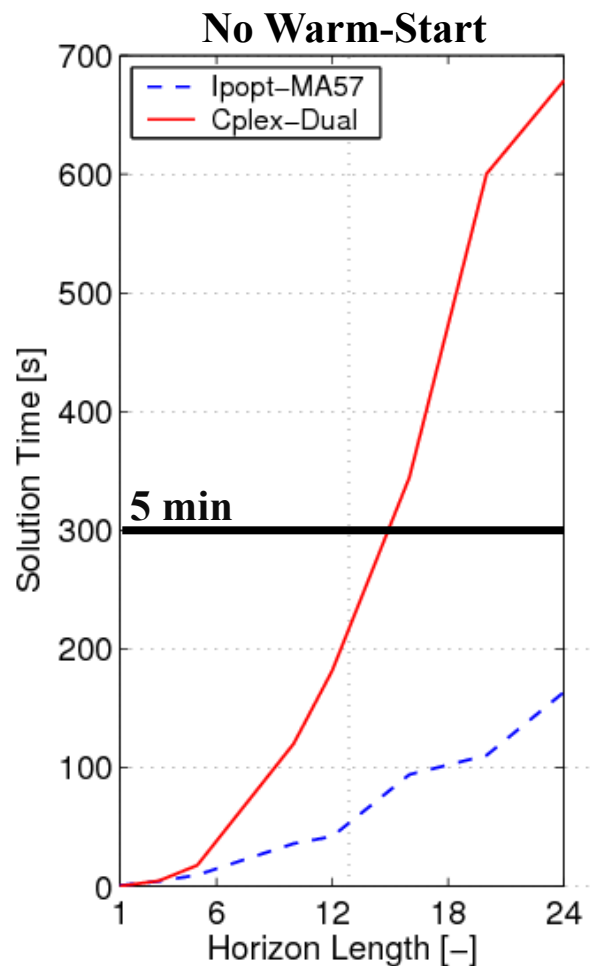


Potential of $\$O(10^8)/Yr$ – Increases with Wind and Demand Variability
Costs Constrained by Solution Time -5 Minutes-

Deterministic Economic Dispatch

Computational Performance – Linear Algebra and Warm-Starts

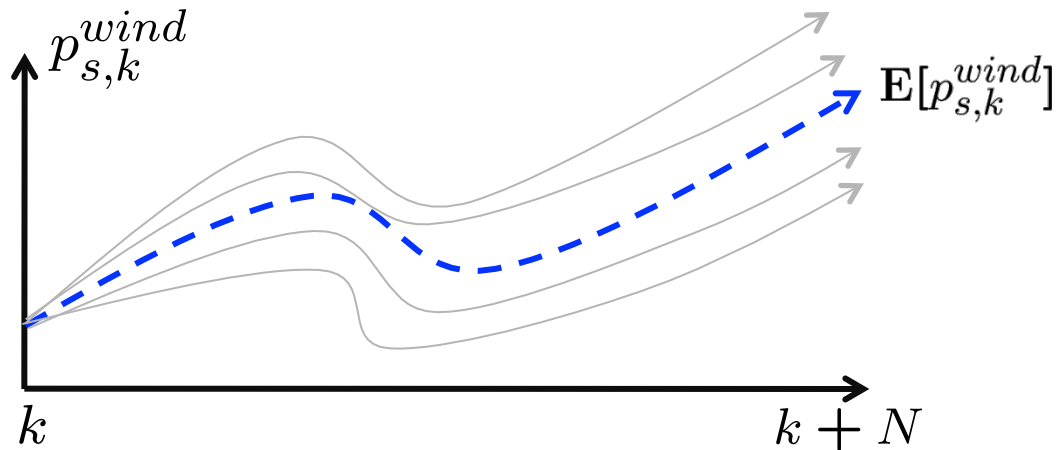
IPOPT - Symmetric KKT Matrix (MA57) vs. CPLEX-Simplex – Unsymmetric Basis Matrix



IPOPT Constructs Basis for Simplex -In Advance, With Forecast Load-
Largest Problem in 5 Minutes - 20 Hr Foresight, 240 Steps, 5 Min/Step, 1x10⁶ Variables

Stochastic Economic Dispatch

Uncertainty Currently Handled Through Reserves – Conservative and Expensive



1st Stage
Current Loads and Wind

2nd Stage
Future Loads and Wind

$$\begin{aligned}
 & \min \quad f(\mathbf{x}) + \frac{1}{S} \sum_{i=1}^S g_s(y_s) \\
 & s.t. \quad \begin{array}{llll}
 A_0 \mathbf{x} & + B_0 y_0 & & = b_0 \\
 A_1 \mathbf{x} & & + B_1 y_1 & = b_1 \\
 A_2 \mathbf{x} & & & + B_2 y_2 = b_2 \\
 \vdots & & & \vdots \\
 A_S \mathbf{x} & & \dots & + B_S y_S = b_S
 \end{array} \\
 & \mathbf{x}, y_0, y_1, y_2, \dots, y_S \geq 0
 \end{aligned}$$

1st Stage Lagrange Multipliers for Network are Implemented Prices

Stochastic Economic Dispatch *Petra & Animescu*

Decompose at Linear Algebra Level – Key for Scalability

- Preserve Convergence Properties (Avoid Lagrangean Relaxation & Benders)
- PIPS Solver: QP/LP Barrier, Schur-Based, Dynamic Load Balancing, MPI

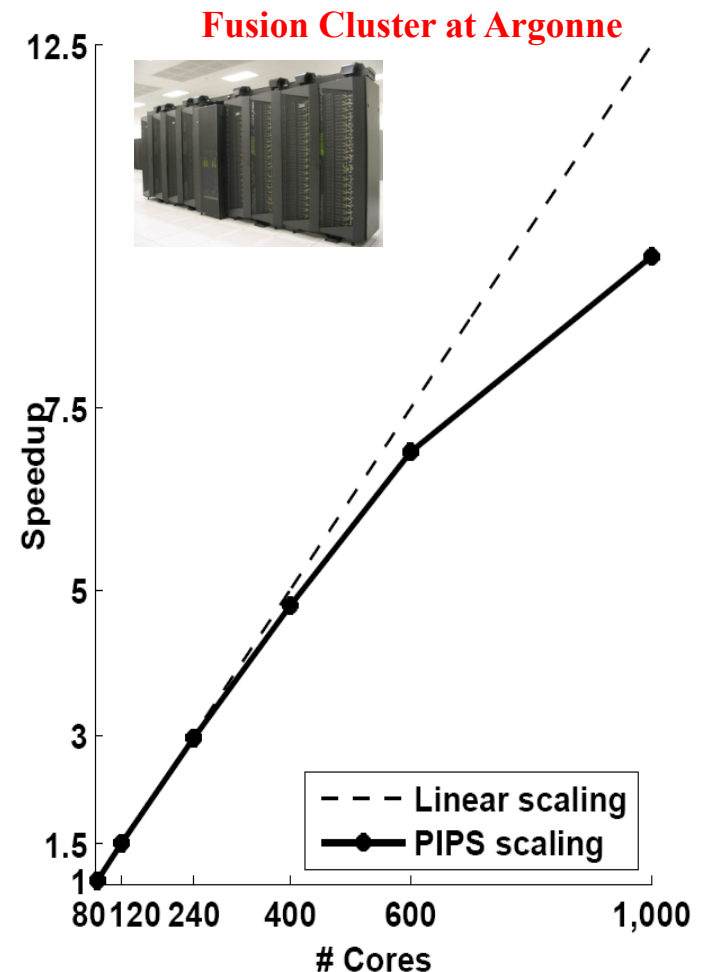
- Dispatch with 150 Generators and 6000 Scenarios, No Network, $O(10^7)$ Variables. 600 Times Faster Than Serial on 1,000 cores

- Scaling Bottlenecks in 1st Stage Dense Schur Complement Avoided with Stochastic Preconditioner

- Strong Scaling on 2,000 cores with $O(10^8)$ Variables and $O(10^5)$ First-Stage Variables – with ScaLAPACK

- **Further Questions:**

- Is Probability Distribution Correct?
- What if Scenario Generation is Expensive?



Uncertainty Quantification – Weather *Constantinescu*

Major Advances in Meteorological Models (WRF)

Highly Detailed Phenomena

High Complexity 4-D Fields (10^6 - 10^8 State Variables)



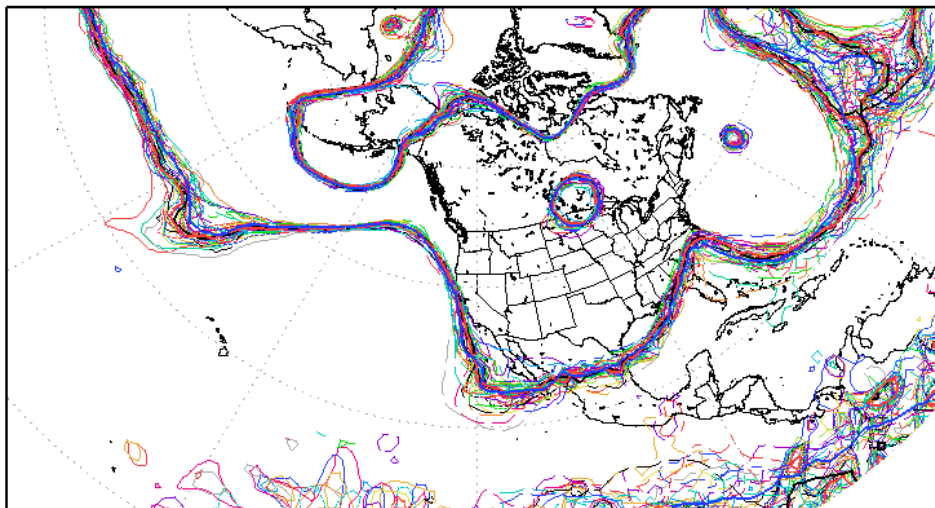
Model Reconciled to Measurements From Meteo Stations

Data Assimilation -Every 6-12 hours-:

3-D Var *Courtier, et.al. 1998*

4-D Var *Navon et.al., 2007*

Extended and Ensemble Kalman Filter *Eversen, et.al. 1998*



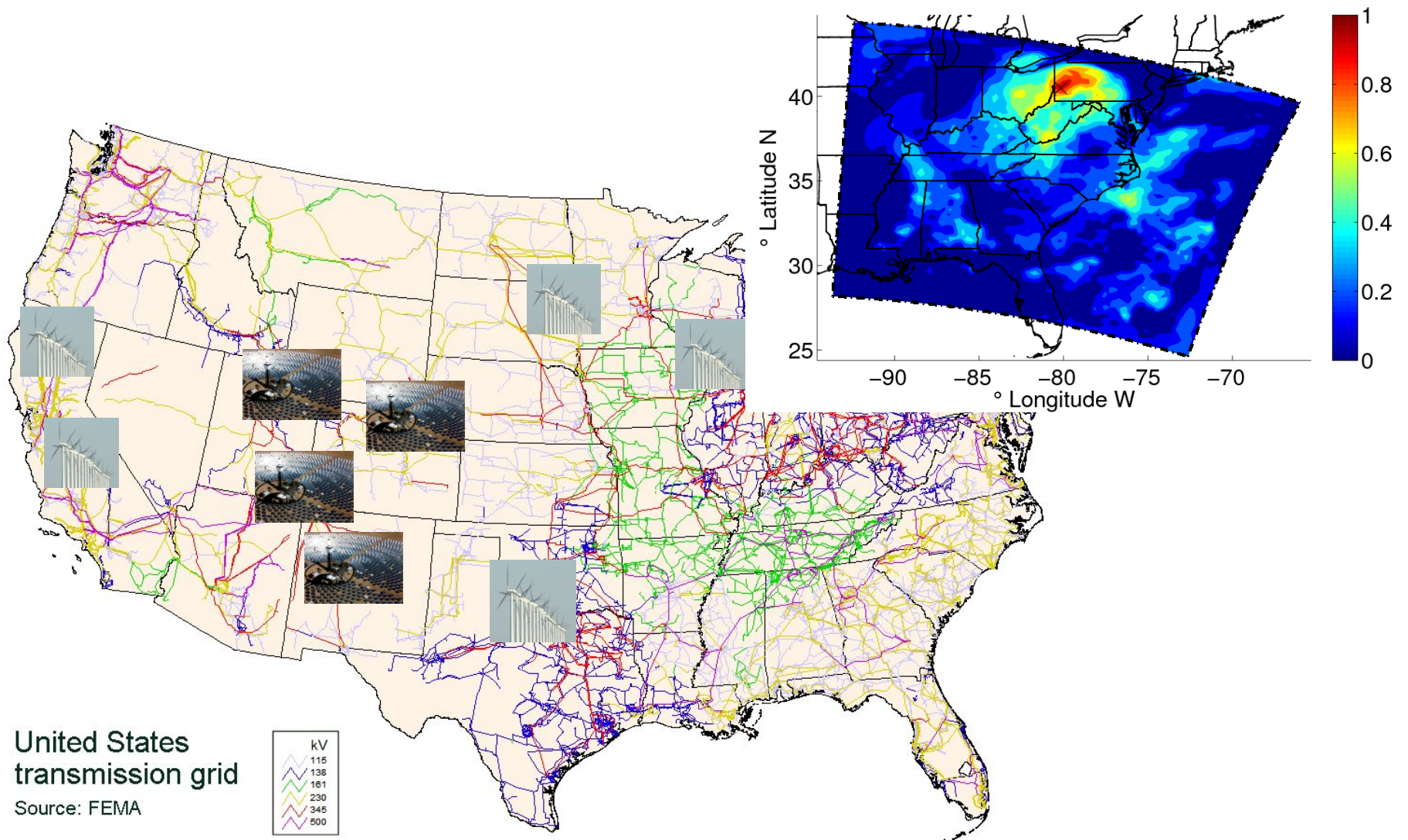
<http://www.emc.ncep.noaa.gov/gmb/ens/>



<http://www.meteo-media.com/>

Is WRF Computationally Practical Enough for Dispatch?

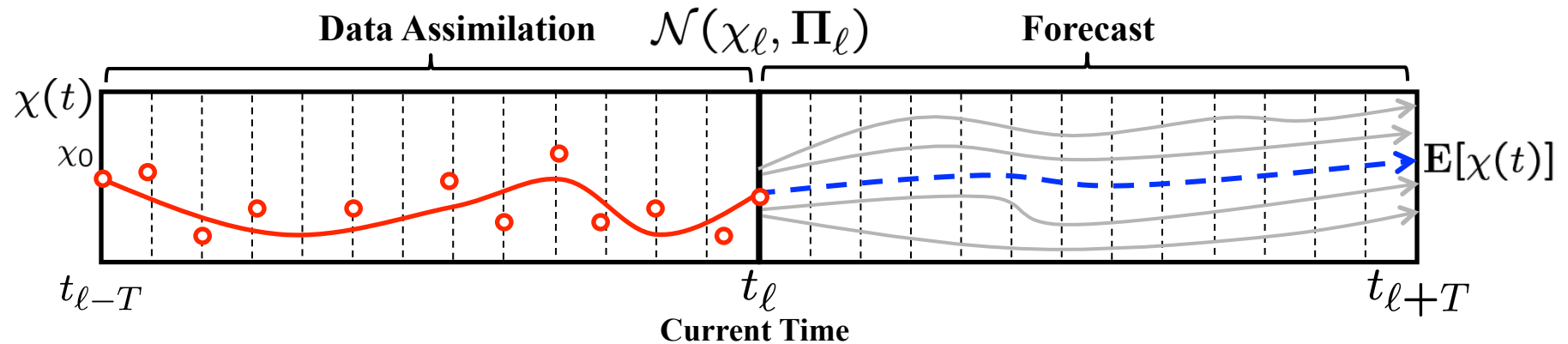
Uncertainty Quantification



Weather, Loads, and Generation Exhibit Complex Spatio-Temporal Correlations

-Correlations Must Be Captured in Forecasting (Not in Practice)-

Uncertainty Quantification

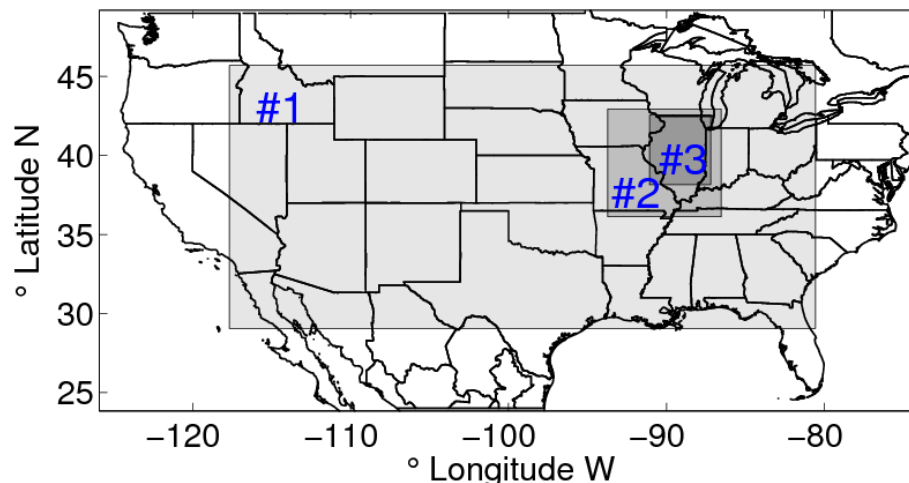


Forming Exact Covariance Matrix is Impractical:

- 1) Create Empirical Distribution using Only Most Relevant States
- 2) Propagate Samples through WRF Model

Making WRF Computationally Feasible:

Grid-Targeted Resolutions and Computational Resources



ID	Size	Grid
#1	130 × 60	32 km ²
#2	126 × 121	6 km ²
#3	202 × 232	2 km ²

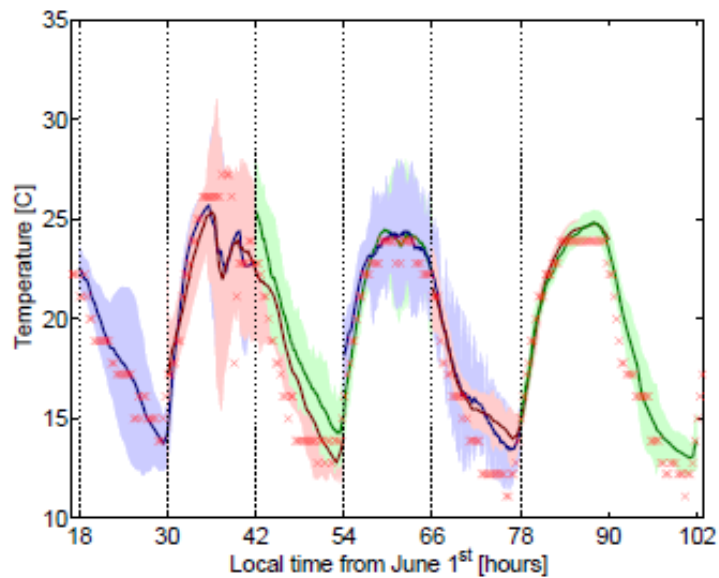
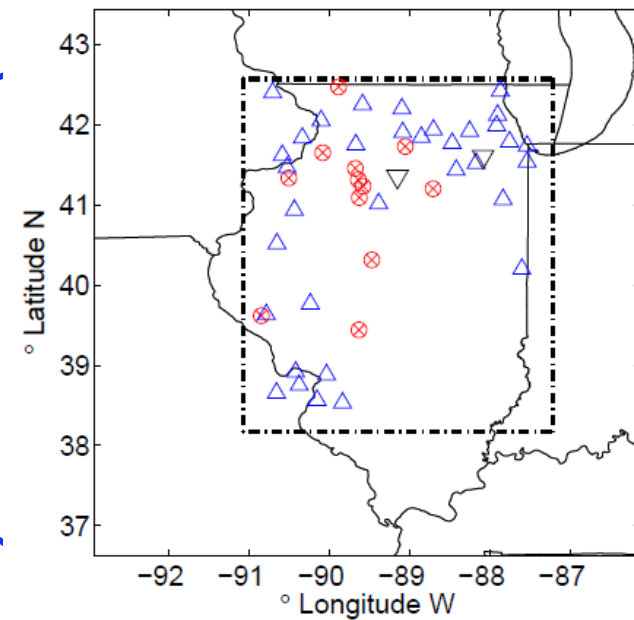
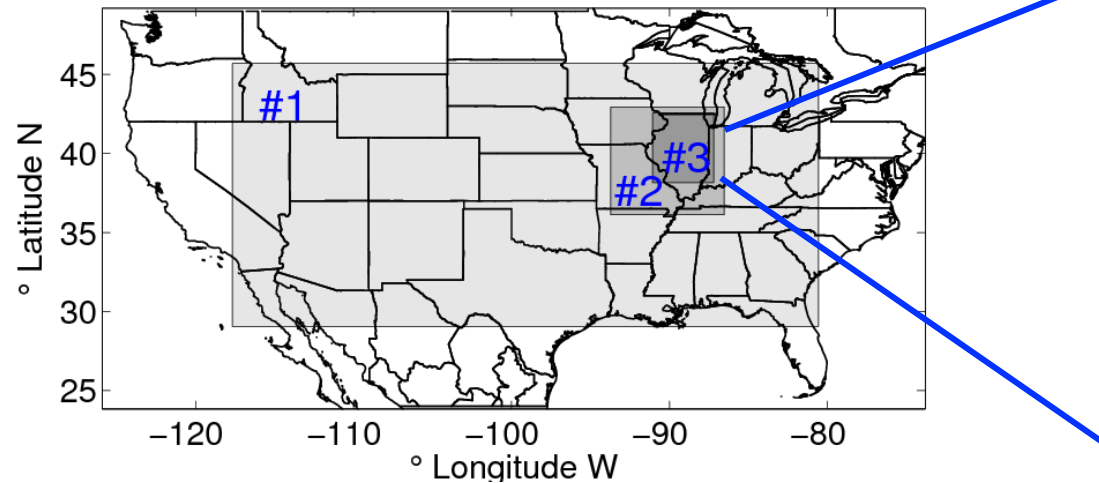
CPU's	Wall-time [hr]
4	50
8	28
16	17
32	10

Jazz Cluster at Argonne National Laboratory

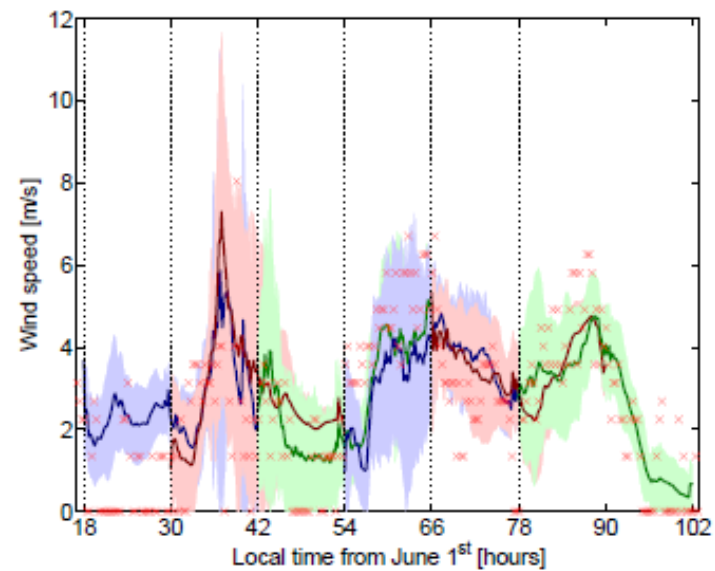
- ✓ Illinois [2km]: 500 processors
- □ US [2 km]: ~50,000 processors
- □ US [1 km]: ~400,000 processors

Uncertainty Quantification

Validation Results (Illinois, 2006) with NOAA Data



Temperature [°C]



Wind Speed [m/s]

Resampling Strategies

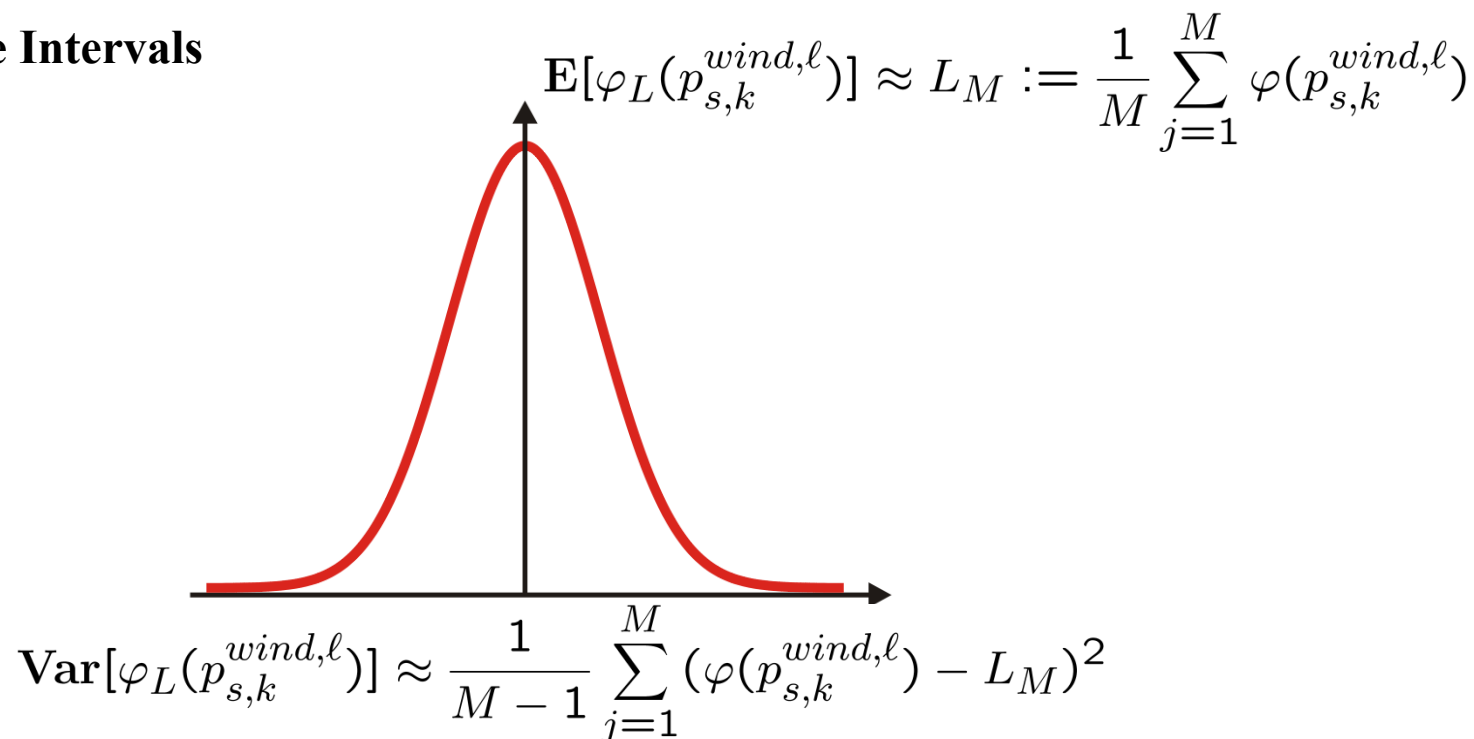
Integration Uncertainty Quantification & Stochastic UC

- WRF Forecast Probability Distribution is NOT in Closed-Form
- Generating Each Scenario is Expensive (50-100 Practical)

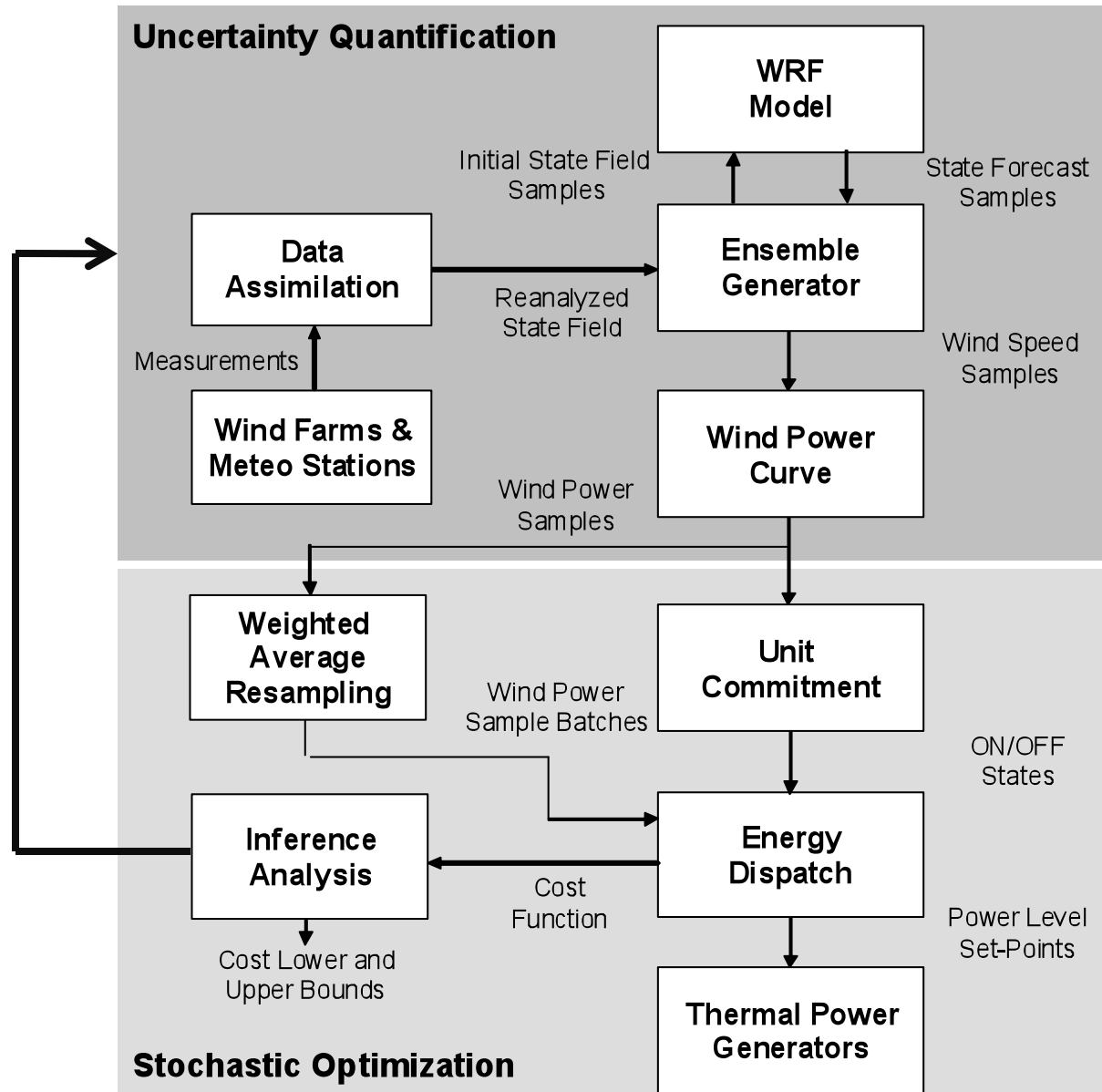
How to Generate More Realizations? Inference Analysis with Resampling

- 1) Sample Weights on Hyperplane $\sum_{s \in \mathcal{S}} w_{s,\ell} = 1$ and Compute $p_{s,j,k}^{wind,\ell} = \sum_{s \in \mathcal{S}} w_{s,\ell} \cdot p_{s,j,k}^{wind}$
- 2) Solve Stochastic Problem with M Batches of Realizations

Cost Confidence Intervals



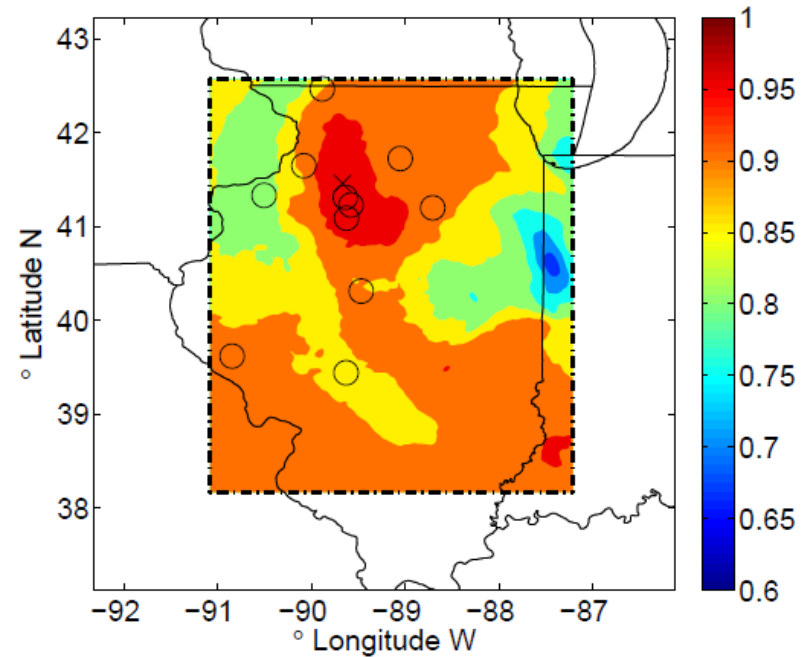
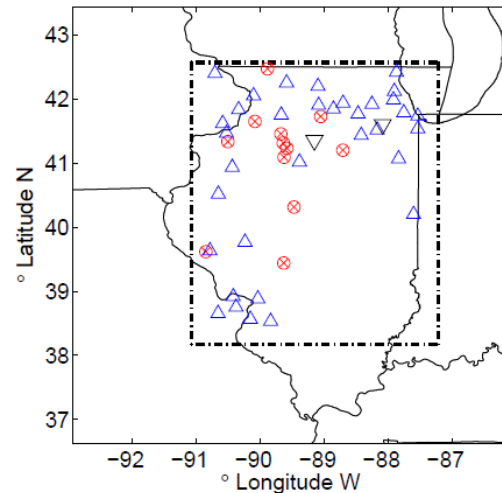
Stochastic Optimization - UQ



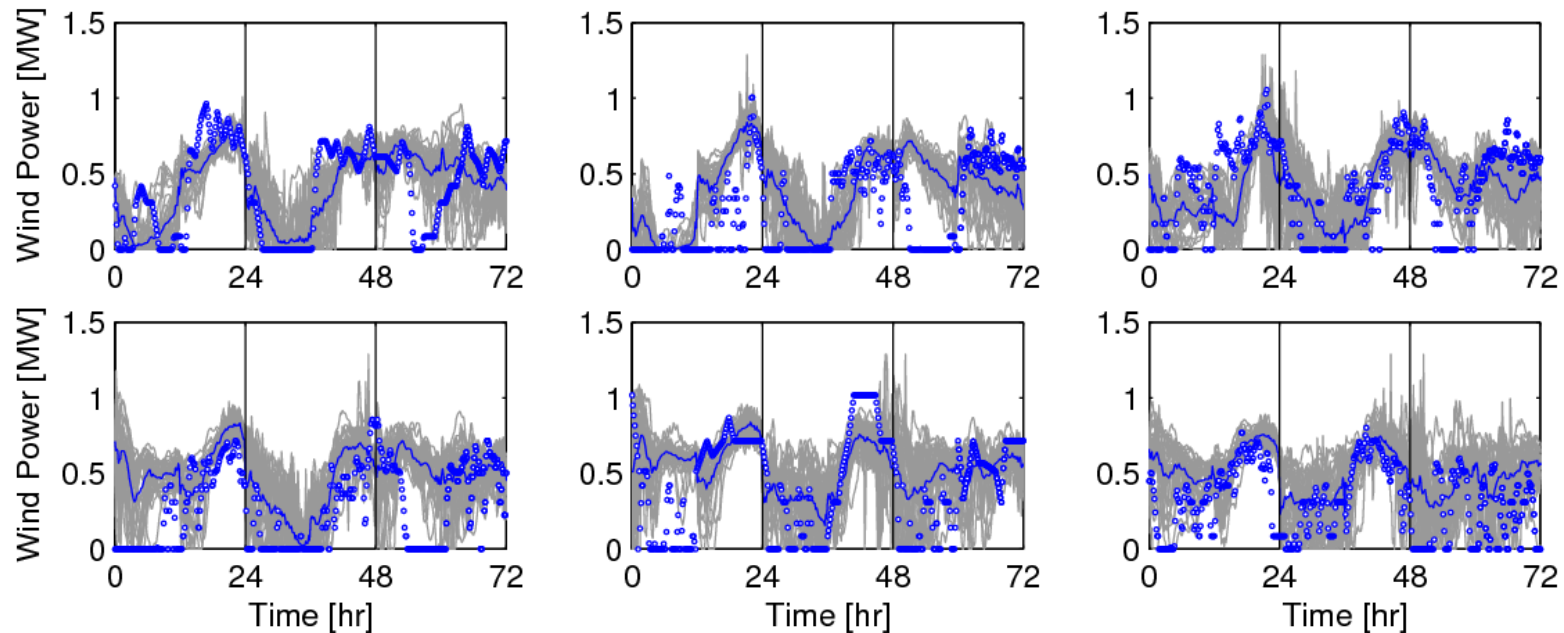
WRF Resolution and Number of Scenarios Must be Adapted in Real-Time

Stochastic Optimization - UQ

Illinois Study (Wind Adoption 20%)

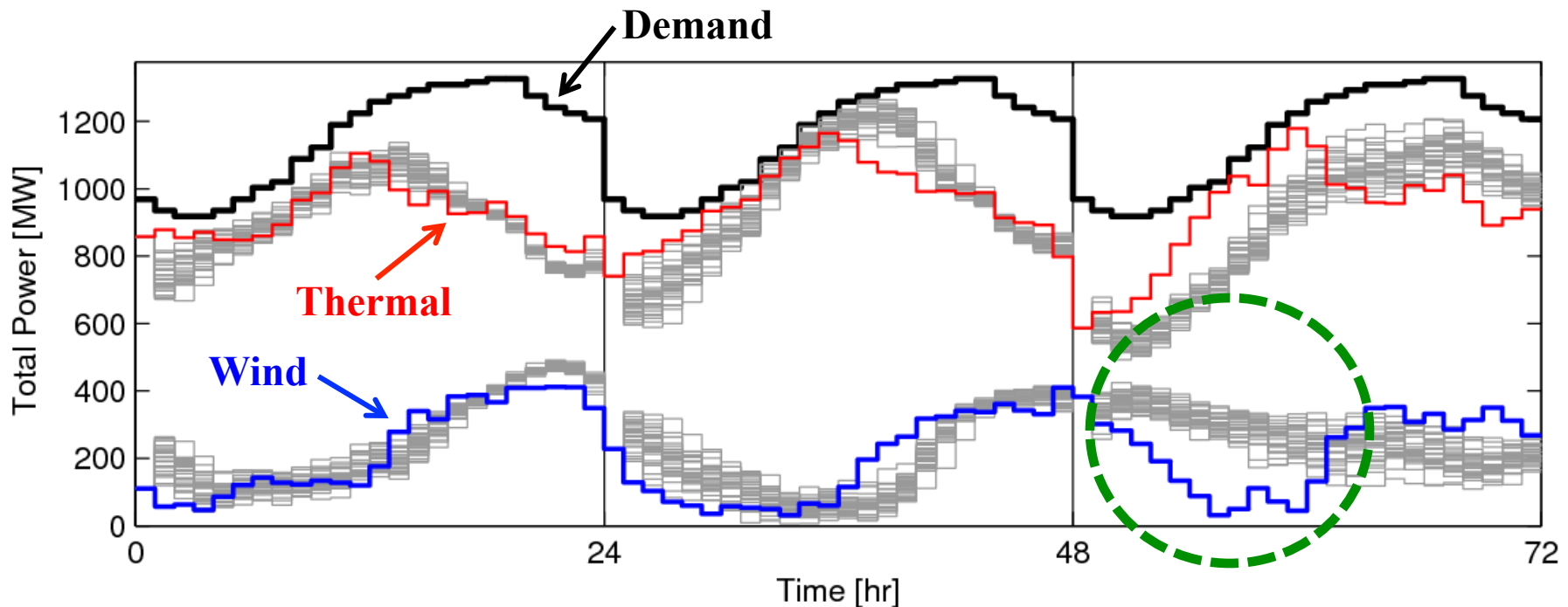


Wind Power Profiles



Stochastic Optimization - UQ

Aggregated Power Profiles -Validation with Real Wind Speed Data-



- WRF Forecasts are -In General- Accurate with Tight Uncertainty Bounds

- Inference Analysis Reveals that 30 WRF Samples are Sufficient

Cost ~ \$474,000, Upper Bound σ^2 (1,082 \$²), Lower Bound σ^2 (1,656 \$²)

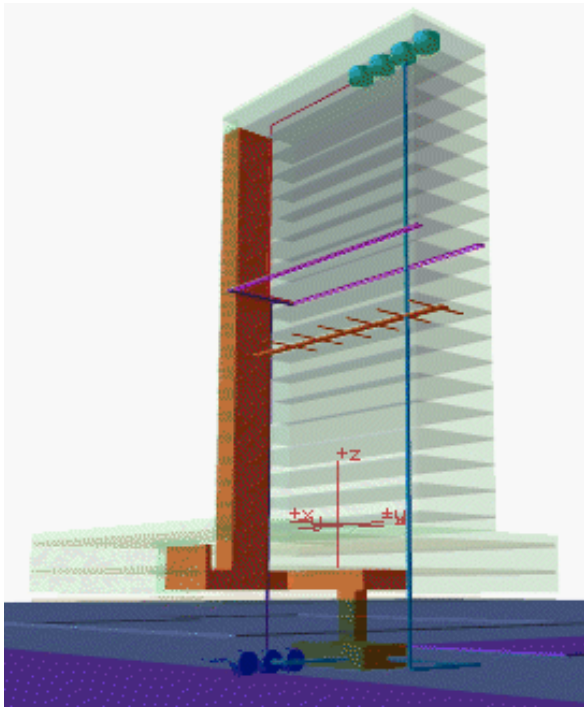
- Excursions Do Occur: Probability Distribution of 3rd Day is Inaccurate!

Higher Frequency Data Assimilation (1 hour)? Missing Physics? 100m Sensors?

Stochastic Optimization Benefits are Limited without UQ

3. Building Energy Management

Building Energy Management



www.columbia.edu/cu/gsapp/BT/LEVER/

Manager: Minimizes Energy Costs in Real-Time
Updates Set-Points Every 5-10 Minutes

$$\min_{u(t)} \int_{t_\ell}^{t_\ell+N} [C_c(t)\varphi_c(t) + C_h(t)\varphi_h(t)] dt$$

$$C_I \cdot \frac{\partial T_I}{\partial \tau} = \varphi_h(\tau) - \varphi_c(\tau) - S \cdot \alpha' \cdot (T_I(\tau) - T_W(\tau, 0))$$

$$\frac{\partial T_W}{\partial \tau} = \beta \cdot \frac{\partial^2 T_W}{\partial x^2}$$

$$\alpha' (T_I(\tau) - T_W(\tau, 0)) = -k \cdot \frac{\partial T_W}{\partial x} \Big|_{(\tau, 0)}$$

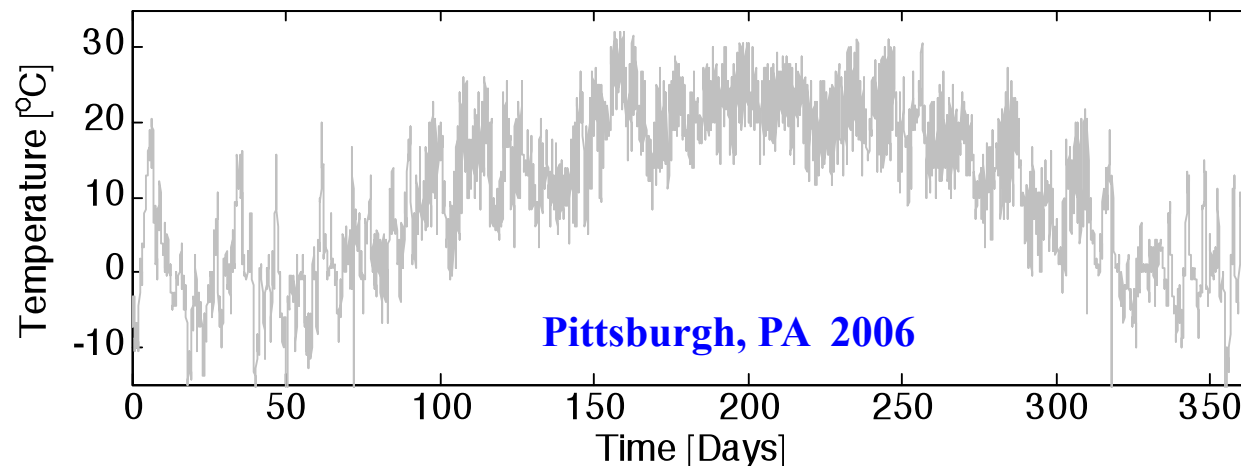
$$\alpha'' (T_W(\tau, L) - T_A(\tau)) = -k \cdot \frac{\partial T_W}{\partial x} \Big|_{(\tau, L)}$$

$$T_I(0) = T_I^\ell$$

$$T_W(0, x) = T_W^\ell(x)$$

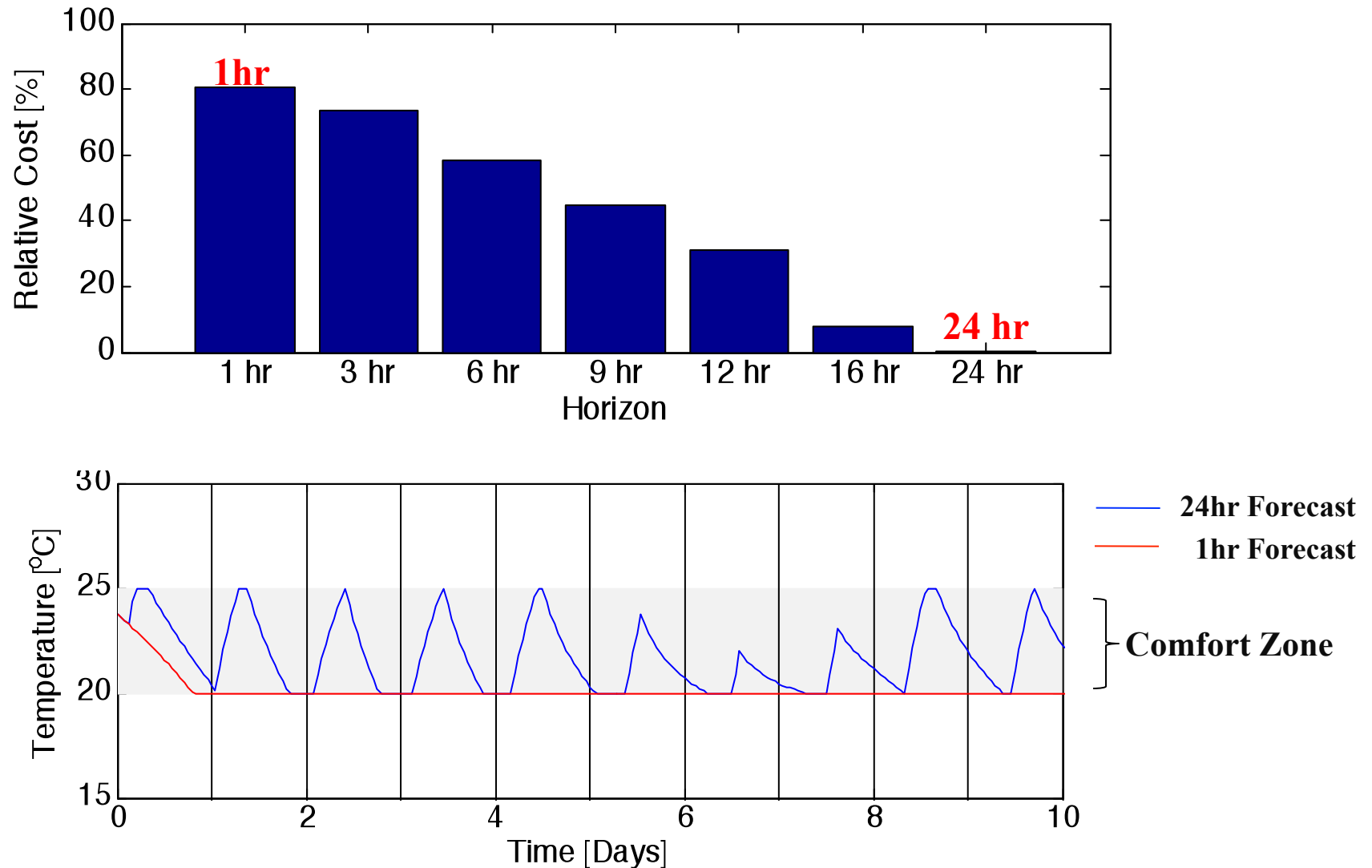
**Dynamic Building
Model (Heat Transfer)**

Energy Demands and Costs Driven by Weather, Occupancy, and Pricing Structures



Building Energy Management

Effect of Foresight on Energy Costs



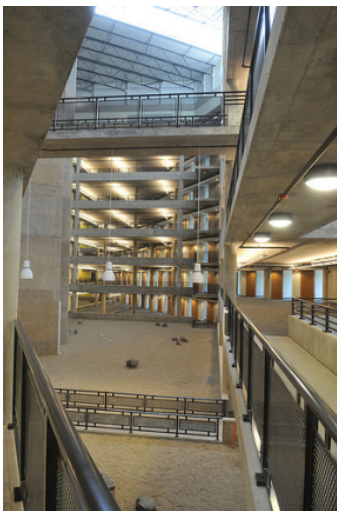
Manager Implicitly Forecasts Demand – Key for Real-Time Pricing & Demand-Response

Building Energy Management

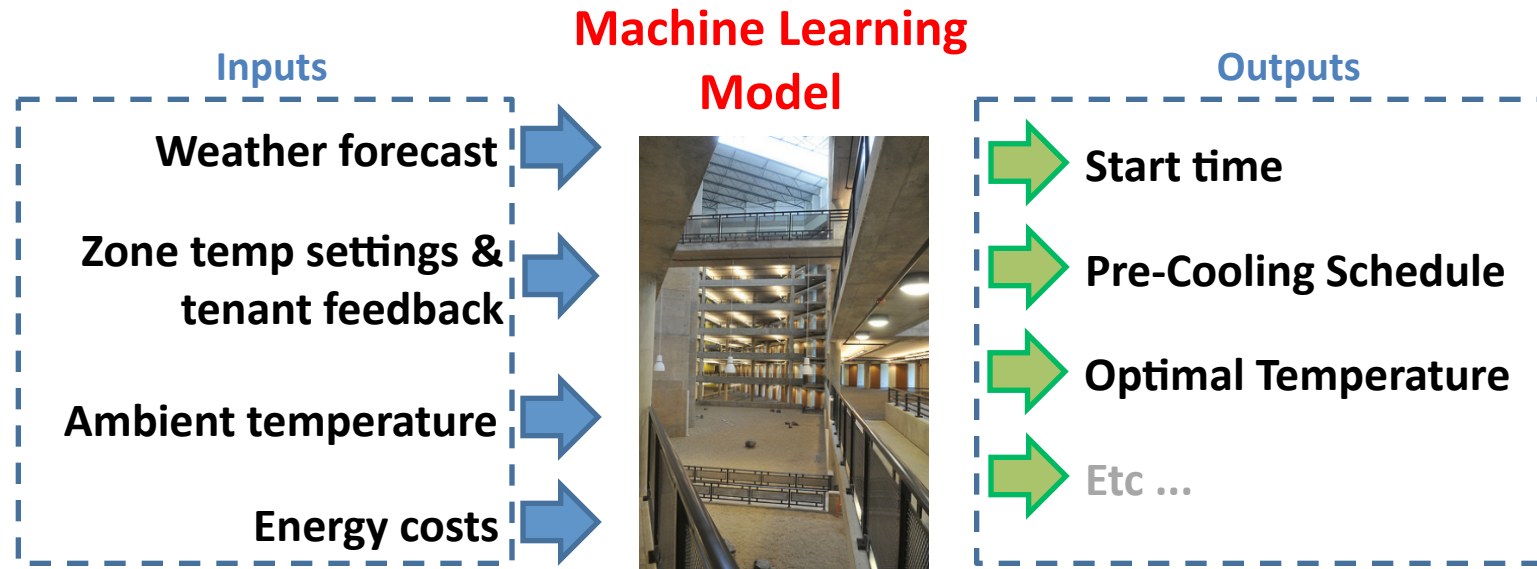


Collaborative Project: Argonne-Building IQ “Proactive Energy Management for Building Systems”

Mike Zimmermann, Tom Celinski, Peter Dickinson (BIQ), and Victor M. Zavala (ANL)

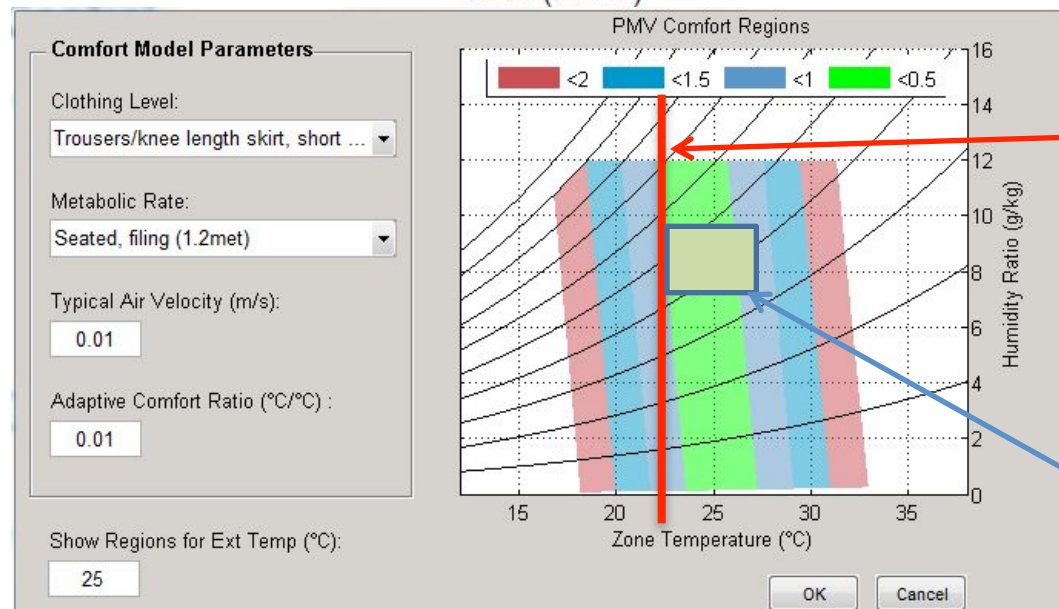
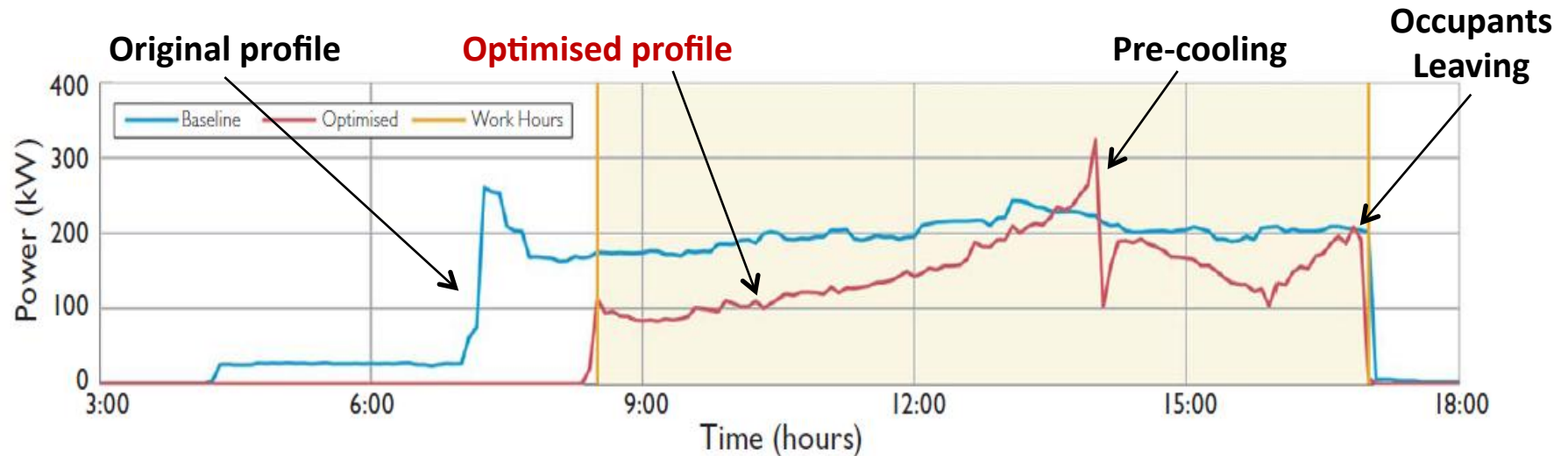


Building Energy Management



- **Solves Nonlinear Optimal Control Problem with Machine Learning Model**
Solved Every 10 Minutes, Forecast of 1-2 Hours
Building Model Re-Trained Daily
Machine Learning Alternative for Large-Scale and Cheap Deployment
- **Key Trade-Off:** Human Comfort vs. Energy Cost vs. CO₂ emissions
- **Computational Challenges:** Increase Building Spatio-Temporal Resolution
Large-Scale and NonConvex Machine Learning
Physics-Based Models? -Michael Wetter-

Building Energy Management

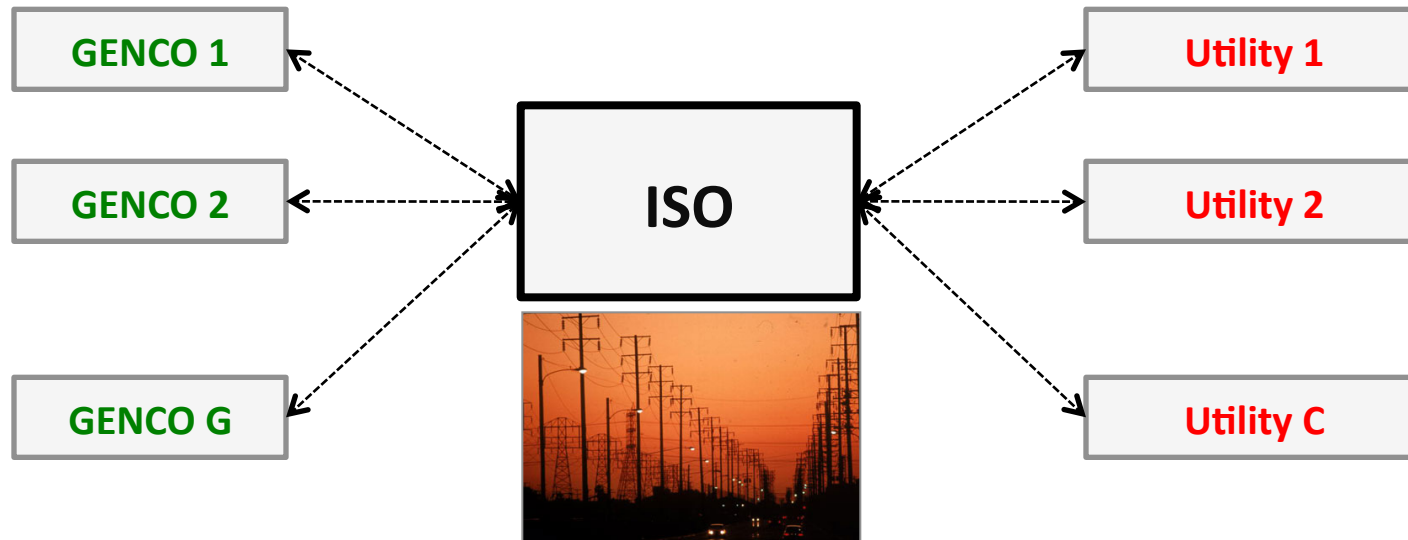


Currently Being Implemented at Argonne's TCS Building – Deployment 12/2010

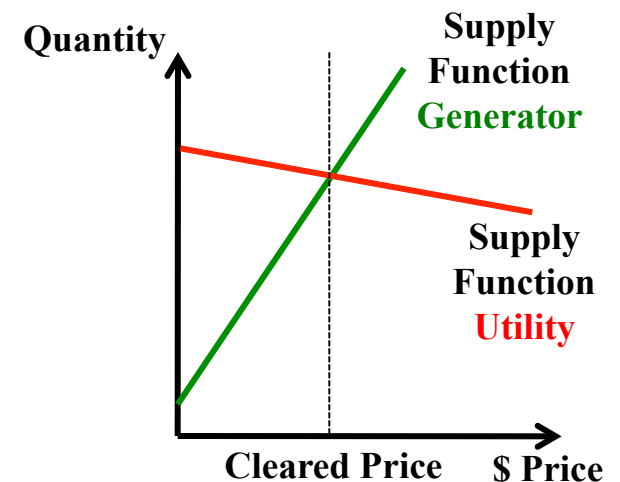
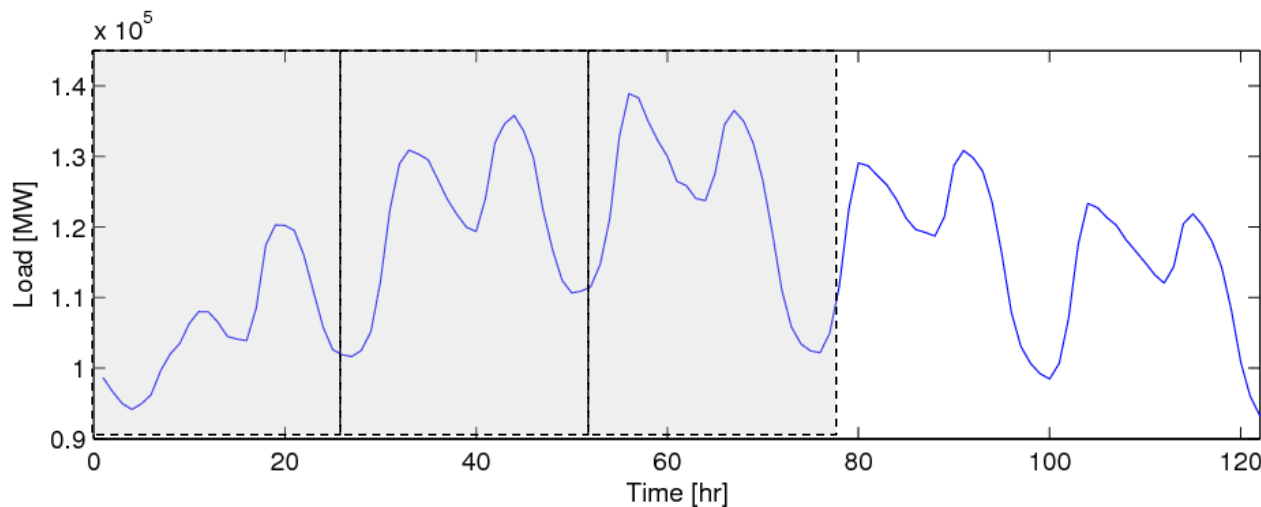
Expected Yearly Savings of 15-30% on HVAC Energy – \$O(10⁵-10⁶)

4. Dynamic Games and Bidding

Dynamic Games and Bidding



- GENCOs and Utilities Bid in Day-Ahead and Real-Time Markets -5 Minutes-
- ISO Clears Markets To Maximize Social Welfare under Transmission Constraints



Key: Generator States Propagated in Time – Ramps and Foresight Affect Market Stability

Dynamic Games and Bidding

Supply Function-Based Dynamic Game Models *Kannan & Zavala, 2010*

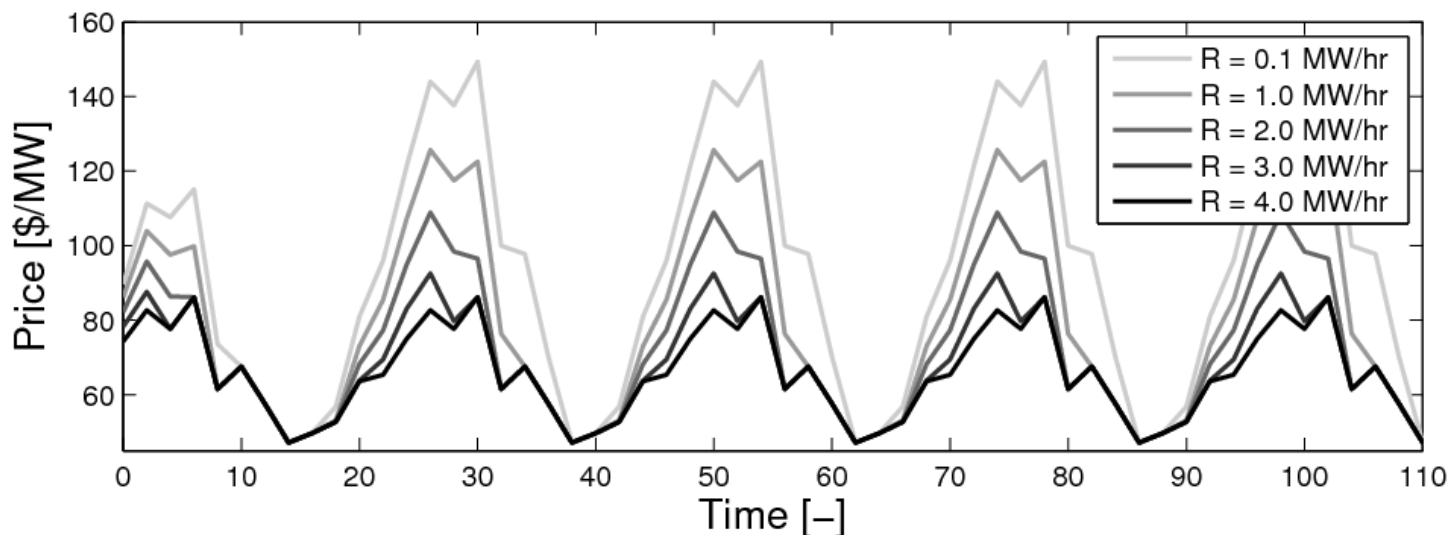
Large, NonConvex Nash and Stackelberg

“Simple” Model: Simultaneous Bidding & Market Clearing, No Transmission, Periodic Load

$$\begin{aligned}
 & \max_{a_i^t, b_i^t, q_i^t} \sum_{t=1}^T \left(\left(\frac{q_i^t + a_i^t}{b_i^t} \right) q_i(t) - C_i(q_i(t)) \right) \\
 & \left\{ \begin{array}{l} s.t. \\ q_i^t \leq cap_i^t \\ q_i^{t+1} - q_i^t \leq R_i^t \\ \frac{q_i^t + a_i^t}{b_i^t} = \frac{c^t + \sum_{i=1}^N a_i^t}{d^t + \sum_{i=1}^N b_i^t} \\ q_i^t \geq 0 \end{array} \right\}, \forall t = 1, 2, \dots, T
 \end{aligned}$$

$\forall i = 1, \dots, P$
Players
Horizon

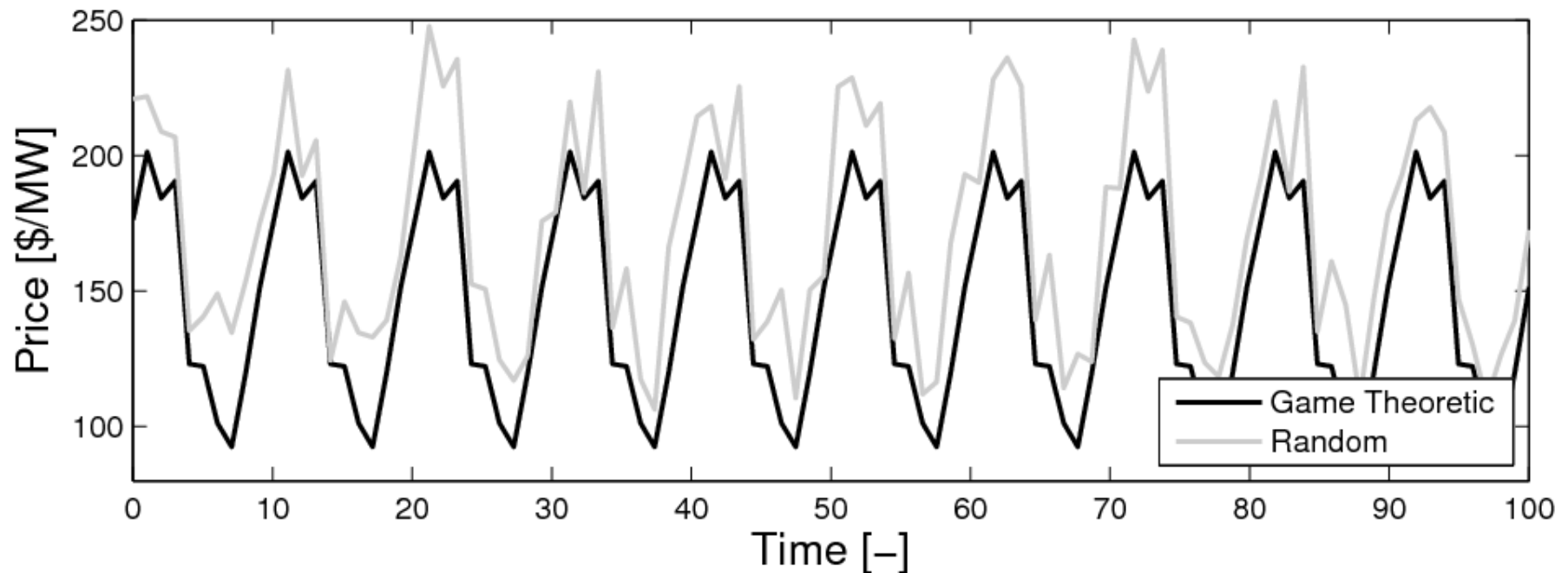
Effect of Ramp Constraints on Market Equilibrium



Dynamic Games and Bidding

Identifying Non-Gaming Behavior

Some Players -Intentionally or Unintentionally- Bid Suboptimally
Introduces Noise in Equilibrium – Can be Inferred from Data



Huge Potential for Dynamic Market Models – Realistic, Price Forecasting

- Fundamental (Existence, Uniqueness, Stability) and Computational Questions

5. Conclusions and Research Challenges

Unit Commitment and Transmission Switching

Day-Ahead Market Clearing, Which Units and Lines Should be Turned ON/OFF?

ED $O(10^5-10^6)$ Continuous + **UC** - $O(10^3)$ Integers + **Switching** - $O(10^4)$ Integers

$$\min \sum_{k \in \mathcal{T}} \sum_{j \in \mathcal{G}} c_j \cdot G_{k,j} \cdot \mathbf{y}_{k,j}^G + c_j^{\uparrow} \cdot (\mathbf{y}_{k+1,j}^G - \mathbf{y}_{k,j}^G) + c_j^{\downarrow} \cdot (\mathbf{y}_{k,j}^G - \mathbf{y}_{k+1,j}^G)$$

$$\text{s.t. } G_{k+1,j} = G_{k,j} + \Delta G_{k,j}, \quad k \in \mathcal{T}, j \in \mathcal{G}$$

$$\sum_{(i,j) \in \mathcal{L}_j} P_{k,i,j} + \sum_{i \in \mathcal{G}_j} G_{k,i} = \sum_{i \in \mathcal{D}_j} D_{k,i}, \quad k \in \mathcal{T}, j \in \mathcal{B}$$

$$|P_{k,i,j} - b_{i,j}(\theta_{k,i} - \theta_{k,j})| \leq M_{i,j} \cdot \mathbf{y}_{k,i,j}^L, \quad k \in \mathcal{T}, (i,j) \in \mathcal{L}$$

$$0 \leq G_{k,j} \leq G_j^{\max} \cdot \mathbf{y}_{k,j}^G, \quad k \in \mathcal{T}, j \in \mathcal{G}$$

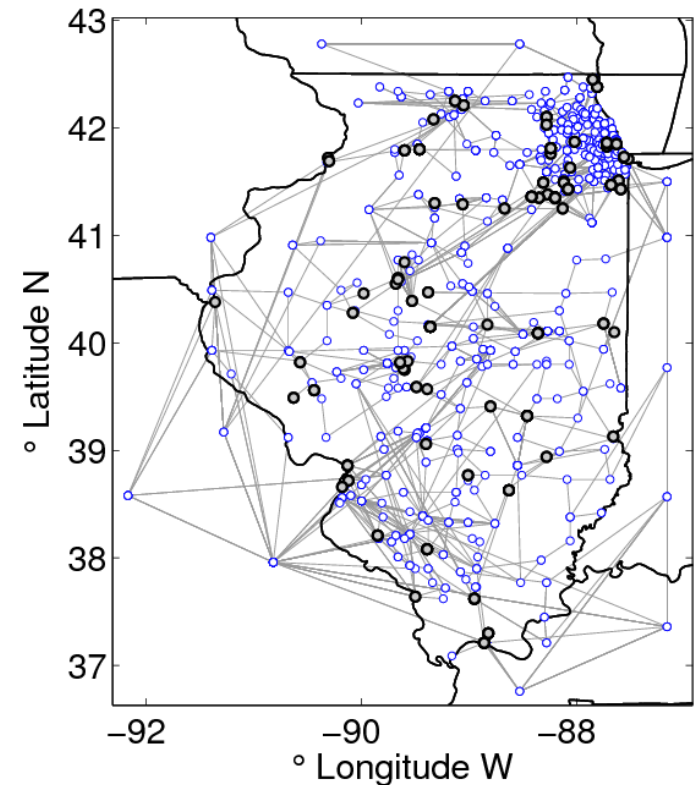
$$|\Delta G_{k,j}| \leq \Delta G_j^{\max} \cdot \mathbf{y}_{k,j}^G, \quad k \in \mathcal{T}, j \in \mathcal{G}$$

$$|P_{k,i,j}| \leq P_{i,j}^{\max} \cdot \mathbf{y}_{k,i,j}^L, \quad k \in \mathcal{T}, (i,j) \in \mathcal{L}$$

$$|\theta_{k,j}| \leq \theta_j^{\max}, \quad k \in \mathcal{T}, j \in \mathcal{B}$$

$$\sum_{\ell=k}^{k+UT-1} \mathbf{y}_{\ell,j}^G \geq UT (\mathbf{y}_{k+1,j}^G - \mathbf{y}_{k,j}^G), \quad k \in \mathcal{T}, j \in \mathcal{G}$$

$$\sum_{\ell=k}^{k+DT-1} (1 - \mathbf{y}_{\ell,j}^G) \geq DT (\mathbf{y}_{k,j}^G - \mathbf{y}_{k+1,j}^G), \quad k \in \mathcal{T}, j \in \mathcal{G}$$



Further Extensions: Stochastic, Complementarity, AC Power Flow

Conclusions and Research Challenges

Next-Generation Grid

- Higher Frequency Forcings – Dynamic Models, Solution Time, Foresight

Many Advances in Stochastic Optimization But Not On Uncertainty Quantification

- Low Cost Weather Forecasts for ISOs, GENCOs, RTOs, Buildings?

WRF -Resolution Constrained by Computational Resources

Machine Learning (Gaussian Process Modeling) - Increase Data Sets

- Limited Uncertainty Information?

High-Performance Computing and Scalable Algorithms

- Expand Domains -Interconnects-, Networks, Linear Algebra + MILP/MINLP
- Lineal Algebra in Simplex, Structure-Preserving Branch & Cut
- Distributed Optimization -Limited Information Exchange-

Optimization Challenges in the Next-Generation Power Grid

Victor M. Zavala

Argonne Scholar
Mathematics and Computer Science Division
Argonne National Laboratory
vzavala@mcs.anl.gov

M. Anitescu, E. Constantinescu, C. Petra, and A. Kannan

**ICiS Optimization in Energy Systems Workshop
August 3rd, 2010**

